MANUAL CONTROL SYSTEMS RESEARCH

I. Introduction

Since Oakland University submitted its original proposal to NASA/ERC, several things have occurred at the University which have directly affected the course of manual control systems research at the institution. Briefly these changes are:

(1) The School of Engineering has installed a Hybrid computing facility consisting of an IBM 1130 digital computer and an EAI 680 analog computer with the EAI 693 interface package. Due to the new dimensions this equipment adds to the area of system identification, it is felt that all future research in this area should be designed to make optimum use of the Hybrid facility. The wide range of computational techniques made possible by the Hybrid computer includes all state-of-the-art analog and digital techniques, such as: continuous parameter tracking, regression analysis, orthogonal filtering and describing functions. Additionally, the IBM 1130's core memory interfaced with the high speed analog capability of the EAI 680 enables the repetitive analysis of large amounts of data in very short periods of time. This iterative property can be used to obtain faster parameter identification than is possible

by any one-pass analog scheme. It will be shown later in this chapter how the Hybrid computer is being used to greatly improve the continuous parameter tracking method of parameter identification.

(2) Robert White, a last-semester engineering student at Oakland University, has designed and built an arm movement control stick. This unit, which is now operational, is interfaced with the Hybrid facility and enables the on-line testing of subjects using analog, digital and/or Hybrid techniques. Through the disc storage unit on the IBM 1130, off-line data analysis is also possible if this form of analysis proves desirable. Figure 1 is a photograph of Oakland University's Hybrid facility with the arm movement control stick in the foreground.

(3) Glenn A. Jackson recently completed a preliminary study into one aspect of the optimal properties of the human operator. This research was conducted under a National Science Foundation Grant [1] and a copy of the terminal report is attached, since it is undoubtedly of interest to NASA/ERC. The main conclusion of this study was that all human operators appear to adjust their mode of operation to minimize the same control cost functional, while they are controlling low order compensatory systems. There

Figure 1: The Oakland University Hybrid Computer Facility with Arm Movement Control Stick.

are several interesting extensions to this work, to be discussed later, which can be studied in conjunction with other aspects of the present research project.

II. Manual Control Research Activities

Several avenues of research are actively being pursued in the manual control area at the present time. This work builds directly on the work of Jackson on the above mentioned NSF project. We feel that this NSF report is an important factor in the excellent cost effectiveness achieved on this NASA/ERC contract. For the past month and for the remainder of this contract it is expected that Jackson will devote his full efforts on the NASA/ERC tasks.

The two projects discussed below deal with fast parameter identification methods. Fast parameter identification is of great interest to people working with systems containing a human operator, since the human is highly adaptive and is known to modify his mode of operation when any system characteristic is changed. In systems where any change in the operator's characteristics could have drastic consequences, such as those changes which occur in a pilot when his aircraft handling properties change, fast parameter identification could be the difference between life and death. Also, for basic research purposes, it is of interest to determine how the human operator adapts when he is confronted with sudden changes in the system he is controlling.

The projects being investigated represent different approaches to the development of high speed identification techniques which can be used to monitor the changes which occur in the human operator while he is controlling low order systems. These methods have potential applications in such manual control systems as attitude control of aircraft, attitude control of spacecraft during re-entry, and automobile steering in the face of wind gusts.

Project 1:

White, under the direction of Jackson, is developing an identification technique which is essentially a Hybrid modification of the continuous parameter tracking method previously developed by Jackson [2]. Two variations of this method are to be investigated, both variations using the crossover model [3] as the basic compensatory system model. The object in each case is the on-line identification of the crossover model parameters K and τ. This identification will be possible over short intervals of time, so that any sudden changes in human operator characteristics will be detected a few seconds after they occur.

A. Continuous Parameter Tracking Variation 1:

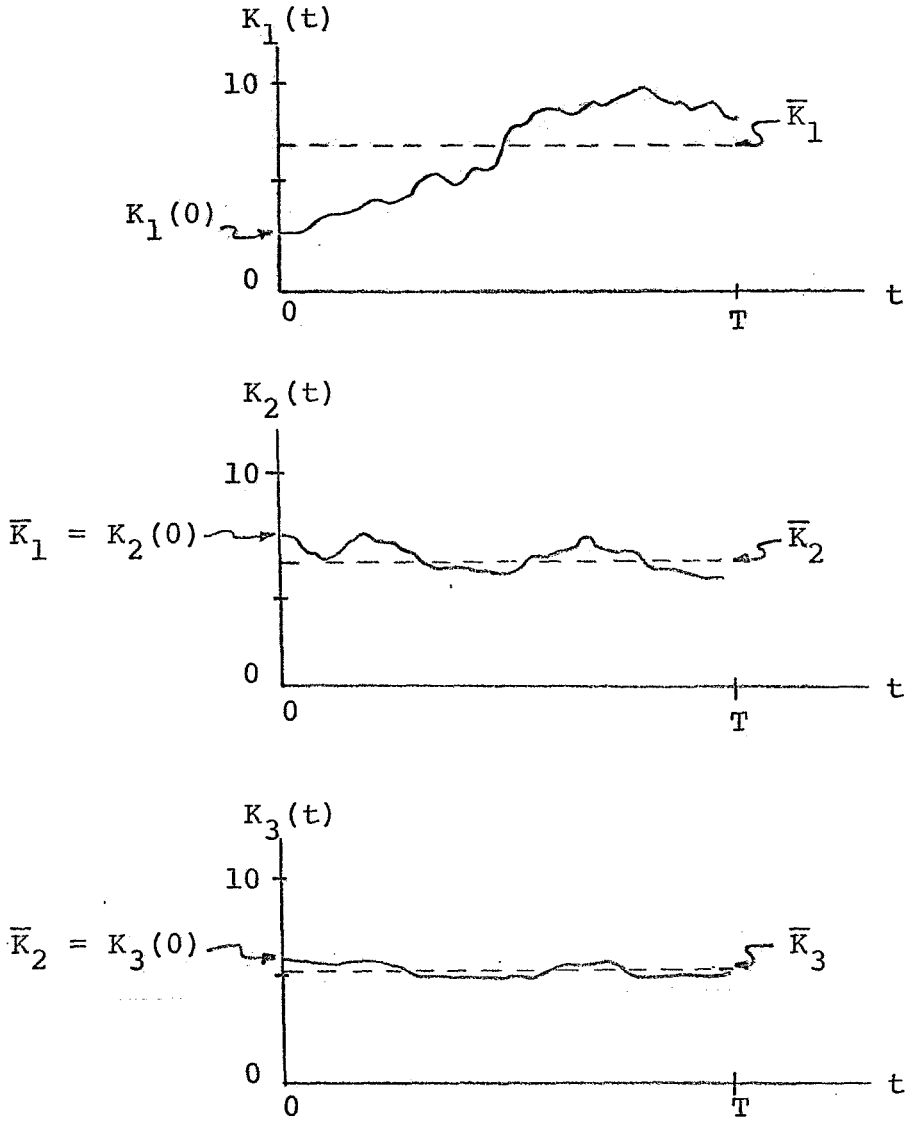
In this method the compensatory system input and output, $\theta_i(t)$ and $\theta_o(t)$, are sampled for a short period of time (5 - 10 seconds) with the samples being stored in the IBM 1130. During the next time interval (<1 second) the stored values will be fed into a fast-time,

analog, continuous parameter tracking model of the compensatory system (i.e., a crossover model). However, since 5 - 10 seconds worth of data are not sufficient for a parameter tracking system to converge in the face of noise [2], the fast-time system will iterate through the same data several times. The initial values of K and τ for the $(n + 1)^{st}$ iteration will be the average values of K(t) and $\tau(t)$ determinated during the n^{th} iteration:

$$K_{n+1}(0) = \frac{1}{T}\int_{o}^{T} K_n(t)\,dt = \overline{K}_n$$

$$\tau_{n+1}(0) = \frac{1}{T}\int_{o}^{T} \tau_n(t)\,dt = \overline{\tau}_n$$

Additionally, the gradient gains used in the parameter adjusting networks for K(t) and $\tau(t)$ will be systematically reduced after each iteration to insure smooth convergence even if a considerable amount of noise is present. It is felt that only 5 or 6 iterations will be required to give satisfactory convergence. Figure 2 shows postulated plots of what the parameter K(t) will look like for three iterations on the fast-time model. ($\tau(t)$ will have comparable plots.) The reduction in the amount of fluctuation in the successive plots is a direct result of the parameter adjustment loop gain reduction.



a) $K_i(t)$ = parameter tracking value of K during i^{th} iteration.

b) T and t are time-scaled variables here.

c) The estimated value of K is $\bar{K}_n$ from the last iteration.

Figure 2: Convergence of Parameter K(t) for Three Iterations of the Tracking Data.

Utilizing this method the average value of a parameter existing over the interval $[t_1, t_1 + T]$ will be known at $t = t_1 + T + T_I$, where T_I is the total iteration time required by the fast-time tracking system. The real-time sampling followed by the fast-time iteration will be repeated over and over during each subject's tracking task. A time-sequence plot of the basic method is given in Figure 3. Again, only the K estimate is shown for simplicity.

B. Continuous Parameter Tracking Variation 2:

In this method the real-time sampling of the compensatory system and the fast-time iterations into the continuous parameter tracking model will be done simultaneously. The compensatory system under test will have its input and output sampled at a fixed rate. Call these samples $\theta_i(n\Delta t)$ and $\theta_o(n\Delta t)$, respectively. If it is assumed that N samples are used during each fast-time iteration, then the input and output signals to the fast-time parameter tracking system during the first iteration will be

$$\sum_{n=1}^{N} \theta_i(n\Delta t)\ \delta(t_o - n\Delta t) \quad \text{and} \quad \sum_{n=1}^{N} \theta_o(n\Delta t)\ \delta(t_o - n\Delta t)$$

respectively. (t_o is the time-scaled time variable,

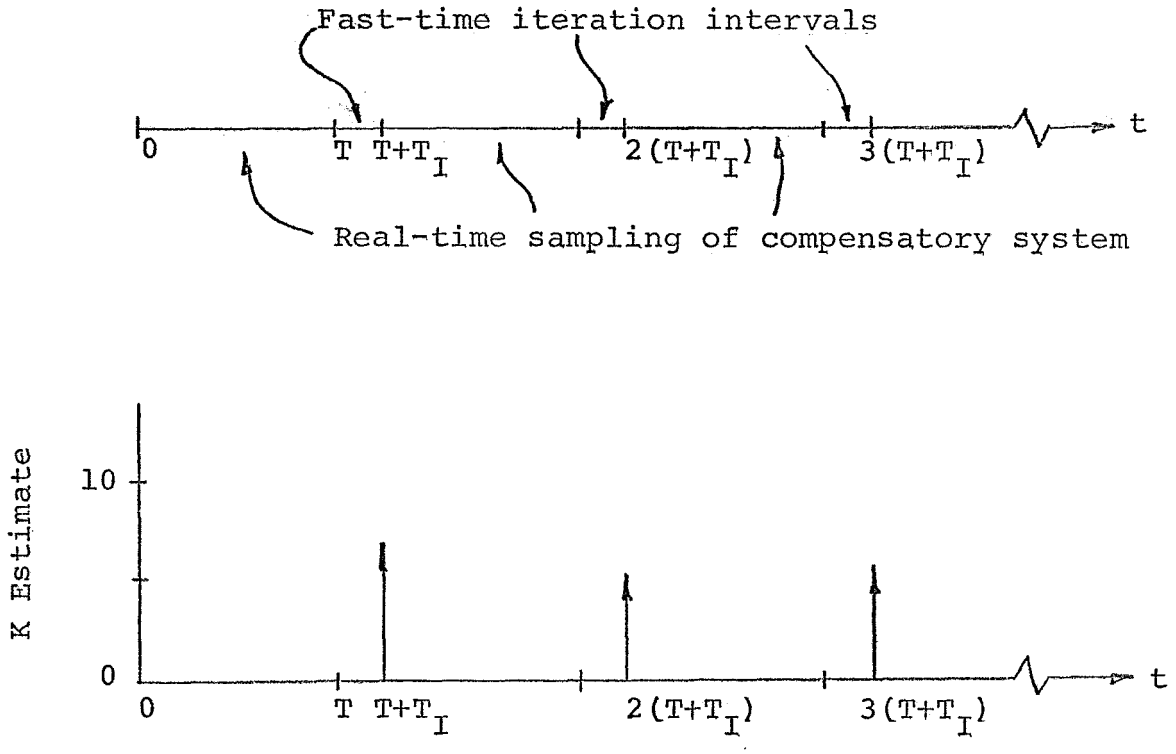


Figure 3: A Time-Sequence Plot Indicating When Parameter Estimates are Determined.

and $\delta(t_o - n\Delta t)$ is a delta function located at $t_o = n\Delta t$.) While this first fast-time iteration is being made, d new samples of $\theta_i(t)$ and $\theta_o(t)$ from the real-time system will have been taken. Thus, the second iteration of the fast-time model can use input and output signals of

$$\sum_{n=k+d}^{N+d} \theta_i(n\Delta t)\ \delta(t_o - n\Delta t) \text{ and } \sum_{n=k+d}^{N+d} \theta_o(n\Delta t)\ \delta(t_o - n\Delta t).$$

Each iteration will therefore use d new data points while discarding an equal number of the oldest data points stored. The gradient gains in the tracking system will again be cycled up and down in order to obtain good convergence. This particular Hybrid version of continuous parameter tracking will not be investigated until version 1 has been fully tested, since some type of time-sharing technique will have to be developed before it can be implemented.

Project 2

Jackson is developing an iterative Hybrid identification technique utilizing estimates by stochastic approximation [4]. In particular, parameter adjustments will be made using the Keifer-Wolfowitz algorithm discussed by Bekey and Neal at the 5th Annual Manual Control Conference [5].

This is also an on-line Hybrid identification method which will operate on short lengths of sampled data from the input and output signals of the compensatory system. The fast-time implementation will use three different crossover models operating simultaneously on the same stored input and output data taken from the compensatory system. The model parameters will be fixed over each fast-time iteration with the parameters stepwise adjusted after each iteration via the Keifer-Wolfowitz algorithm. During the n^{th} iteration using one set of compensatory system input-output sampled data, Model 1 will have parameters K_n, τ_n; Model 2 parameters $K_n + c_n$, τ_n; and Model 3 parameters K_n, $\tau_n + d_n$. During this n^{th} iteration, three performance indices will be measured:

$$J_{n1} = \int_{t_1}^{t_1+T} ||e_1(t_o, K_n, \tau_n, \theta_i(t_o)||dt_o$$

$$J_{n2} = \int_{t_1}^{t_1+T} ||e_2(t_o, K_n + c_n, \tau_n, \theta_i(t_o)||dt_o$$

$$J_{n3} = \int_{t_1}^{t_1+T} ||e_3(t_o, K_n, \tau_n + d_n, \theta_i(t_o)||dt_o$$

where $||e_i||$ is a norm of the error existing between the recorded compensatory system output and the output of the

i^{th} crossover model. The adjustment, as dictated by the Keifer-Wolfowitz algorithm, is

$$K_{n+1} = K_n + a_n(J_{n1} - J_{n2})/c_n$$

$$\tau_{n+1} = \tau_n + b_n(J_{n1} - J_{n3})/d_n$$

where

$$\lim_{n\to\infty} a_n = \lim_{n\to\infty} b_n = \lim_{n\to\infty} c_n = \lim_{n\to\infty} d_n = 0$$

$$\sum_{n=1}^{\infty}\left(\frac{a_n}{c_n}\right)^2 < \infty \text{ and } \sum_{n=1}^{\infty}\left(\frac{b_n}{d_n}\right)^2 < \infty$$

$$a_n = \frac{A}{n}\ ,\ b_n = \frac{B}{n}$$

$$c_n = \frac{C}{n^{1/6}}\ ,\ d_n = \frac{D}{n^{1/6}}$$

with A, B, C and D positive constants.

The system will iterate on one set of stored data until convergence of the parameters K and τ is achieved. At this time new data will again be sampled from the compensatory system and the process will start again. This will give a time plot similar to that in Figure 3 above. A general block diagram of the method is given in Figure 4.

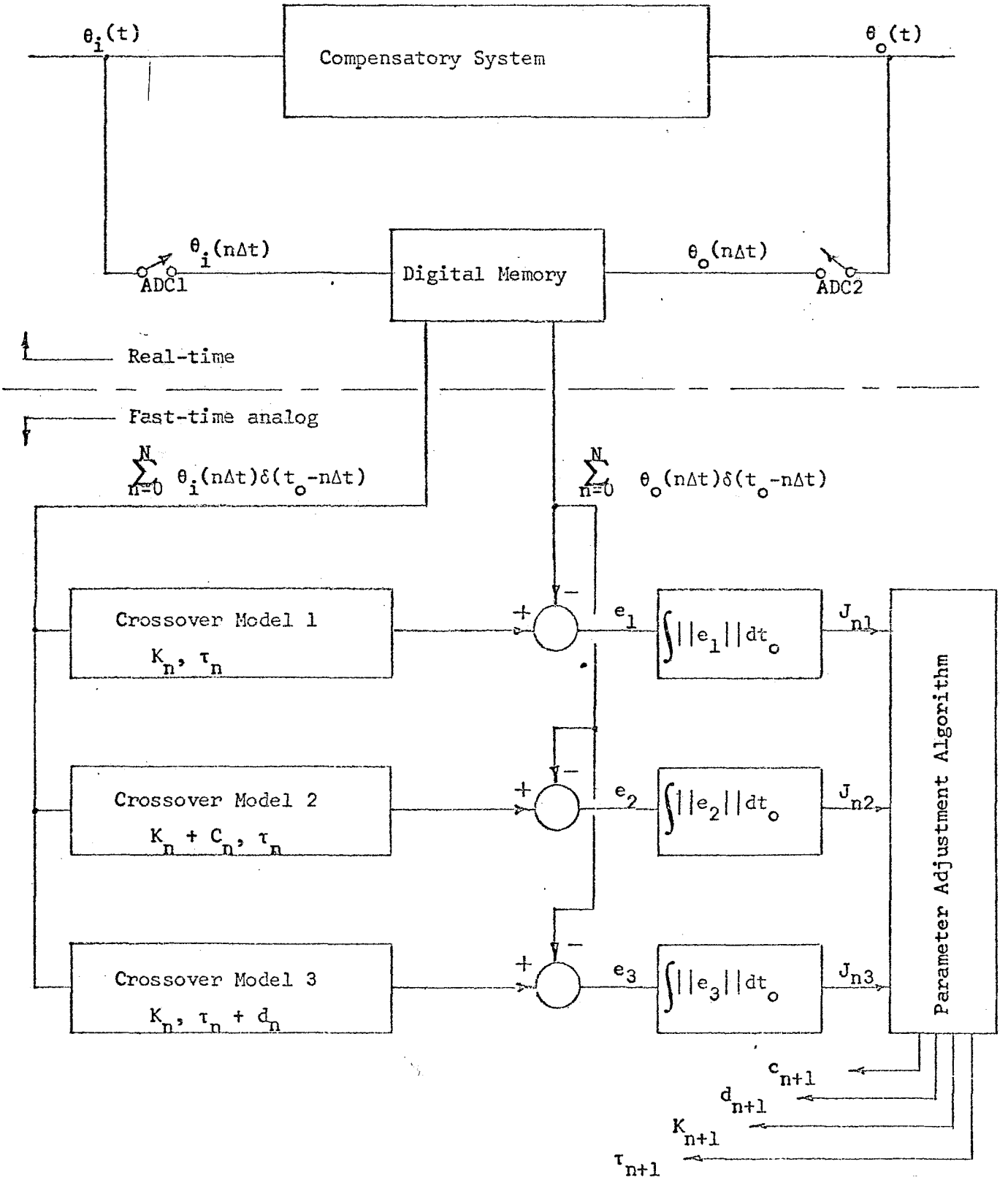


Figure 4: Block Diagram of a Stockastic Approximation Method of Parameter Identification

III. Further Studies

Once the basic identification techniques discussed above have been completely implemented, they will be used as vehicles for several other studies.

First, the basic techniques themselves will be analyzed and, hopefully, improved.

Second, the basic techniques will be used to evaluate the manual control research originally proposed to NASA/ERC with regard to continuous parameter tracking. Namely, can some form of state variable error be used to improve the speed of parameter convergence (rather than using simply output error), and can knowledge of the remnant spectrum [6] be used to filter out those portions of the remnant which cause parameter tracking problems?

Third, the basic techniques will be used to determine average K and τ values for new subjects in order to substantiate, or disprove, Jackson's hypotheses on the optimality of the human operator discussed in his NSF report [1]. In particular, can the changes which are known to occur in the average K and τ values, due to variations in the input signal spectrum, be accounted for by the optimal policy developed in Jackson's report? Jackson's optimal policy fits his original data [2,7], but needs further testing and analysis. These tests can be run at the same time evaluations of the parameter identification techniques are being conducted, and thus double use of the tests can be made.

References

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